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# BRINGING A NEW PERSPECTIVE ON CO-MOVEMENTS OF STOCK MARKETS IN EMERGING ECONOMIES THROUGH CAUSALITY AND WAVELET ANALYSIS

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**JEL classification:** C43, C58, G01

## Abstract

*The recent global financial (and economic) crisis has validated the need to assess the financial sector of the economies with rather unconventional approaches. Believing that financial markets use all the available information in an efficient manner is as questionable as finding models which test the existence of bubbles in stock exchange markets. In this respect, this paper tries to introduce a different perspective by attempting to examine the role of emerging markets in this turmoil period, termed the Great Recession. We are intrigued by the argument that stock exchange markets in emerging economies have been affected in an asymmetric manner. If this so, it is important to identify the markets that felt the effects of the contagion more than the others. The economies included are Brazil, China, India, Indonesia, Russia, South Africa and Turkey and we use the US for purposes of comparison. The data is weekly and runs through January 2003 – March 2014 with many sub-periods for pre and post crisis as necessary. We use both conventional and unconventional methods to analyze the asymmetric contagion argument. These include time domain causality (Granger, 1969), percentage of variance explained (Geweke, 1982), frequency domain causality (Breitung and Candelon, 2006) and wavelet co-movement (Rua, 2010) methods. Our preliminary findings show that the stock exchange markets with rather high concentration of foreign investors is highly affected by the recent global financial crisis. Moreover, the asymmetric contagion*

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*argument is rather verified by different and significant wavelet co-movement results for some emerging economies in the bilateral analysis with the US.*

## **1. Introduction**

The recent technological developments, the facilities of communication, the liberalization activities in terms of economies, the augmentation of international trade, the committed free trade agreements and trading blocks, concisely the fact of globalization, have made economies more integrated among countries. Certainly, some advantages and disadvantages occur with financial integration. For instance, emerging economies have become more attractive places for portfolio investors and portfolio capital. Besides all of these above factors, low transaction costs are also one of the other benefits of this integration. Likewise, the presence of strong economic ties between countries can affect stock market actions over time. However, this integration might cause fragility in terms of economies and these influences might be contagious. Undoubtedly, these can be the disadvantages of the global integration.

In this sense, Rua and Nunes (2009) argue as follows (that):

*“...the study of the comovement of stock market is crucial for risk assessment of portfolios. A higher comovement among the assets of a given portfolio implies lower gains, in terms of risk management, stemming from portfolio diversification. Hence, the evaluation of the comovement is of striking importance to the investor so that he can best assess the risk of a portfolio.”*

The movements of the stock markets have crucial effects on making financial policy and investment decisions.

Finally, Ali et al. (2011) asserts that:

*“... to study comovements among stock markets would be useful for policy makers in a sense if stock markets are found to be closely linked then there is a danger that shocks in one market may spill over to other markets thus require closer cooperation among the authorities of these countries, whose equity markets are closely linked.”*

This study investigates the comovement of the US stock market indices with the selected markets of China, Russia, Turkey, Indonesia, India, South Africa, and Brazil. We use the US stock market as the anchor and employ causality and wavelet comovement analysis. Our data

covers the period 2003 to 2014. We use time domain and frequency domain Granger causality analysis so we can complete the results of these two different methodologies.

Our study is motivated by using new econometric methodology to analyze the dynamic nature of the stock markets that are examined. In this respect, we try to find the similarities and differences of these stock markets which would be the main contribution of this paper.

## **2. Literature Review**

The previous empirical studies of comovements of stock markets have not revealed consistent results because of being dependent on observed time periods – whether they are daily, weekly or monthly. Among those studies, Korajczyk (1996) investigates a measure of the financial integration between equity markets by using multifactor equilibrium arbitrage. He used multifactor equilibrium Arbitrage Pricing Theory to define risk and to measure deviations by applying the integration measure to equities traded in 24 countries (4 developed and 20 emerging) using monthly data. The results show that the measure of market segmentation tends to be much larger for emerging markets than the developed markets. This finding is consistent with larger barriers to capital flows into or out of emerging markets. The measurements often tend to decrease over time which supports the growing levels of integration. Large values of adjusted mispricing also occur around the periods of economic turbulences and the periods in which capital controls change significantly. On the other hand, Elyasiani et al. (1998) investigate the interdependence and dynamic linkages between the emerging capital market of Sri Lanka and the markets of its major trading partners (Taiwan, Singapore, Japan, South Korea, Hong Kong, India and the US) by using vector autoregression (VAR) analysis. The results demonstrate that there is no significant interdependence between the Sri Lankan market and the equity markets of the US and Asian markets.

Husain and Saidi (2000) examine the integration of the equity market in Pakistan with those in selected countries (USA, UK, Japan, Germany, Hong Kong, and Singapore) through co-integration methodology by employing weekly data from January 1998 to December 1993. They detect a long run relationship of the Pakistani market with the markets of the UK and Japan. Accordingly, Ng (2002) investigates the linkages between the South East Asian stock markets and long-run relationships among South-East Asian stock markets over the period 1988-1997. However, correlation analysis indicates that South East Asian stock markets are

becoming more integrated than ever. Moreover, the results from the time-varying parameter model shows that the stock market returns of Indonesia, the Philippines and Thailand have all become more closely linked with Singapore. Likewise, Chen et al. (2003) examine dynamic interdependence of the major stock markets in Latin America by using data from 1995 to 2000. They employ the indices of Argentina, Brazil, Chile, Colombia, Mexico and Venezuela and use co-integration and error correction vector autoregressions (VAR) techniques. They find that there is one co-integrating vector that explains the dependencies in price. Their results suggest that the potentials for diversifying risk by investing in different Latin American markets are limited.

Worthington et al. (2003) examine price linkages among Asian equity markets during the Great Recession. Three developed markets (Hong Kong, Japan and Singapore) and the six emerging markets (Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand) are included in the data set and they use multivariate cointegration and VAR analysis to examine the causal relationships among these markets. Their results show stationary relationships and significant causal linkages are determined between the Asian equity markets. Furthermore, Wong et al. (2004) use weekly stock indices of the major stock Exchange in the US, the UK, Japan, Malaysia, Thailand, Korea, Taiwan, Singapore and Hong Kong. They find that Singapore and Taiwan are cointegrating with Japan while Hong Kong is cointegrating with the US and the UK. There are no long run equilibrium relationship between Malaysia, Thailand and Korea and the developed markets of the US, the UK and Japan.

Gallegati (2006) revisits the issue of integration of emerging markets and of the developed markets with each other over different time horizons by using weekly stock indices data from June 1997 till March 2005 for the five major MENA equity markets (Egypt, Israel, Jordan, Morocco and Turkey). By applying the discrete wavelet decomposition analysis they find that wavelet variance of MENA stock markets tends to decrease and wavelet correlation for among MENA stock markets tends to increase as the wavelet time scale increases. When MENA stock markets are compared with the S&P 500 and the Eurostoxx indices, the results show these countries are neither regionally nor internationally integrated except for Israel and Turkey. Morana and Beltratti (2008) employ monthly data from stock market indices of US, UK, Germany and Japan to assess the linkages during the period from 1973-2004. Their findings show that the linkages have in general grown stronger over time particularly in the US and Europe and that there is a progressive integration among those stock markets.

Rua and Nunes (2009) focus on the wavelet comovement analysis both for the aggregate and sectoral levels of the markets of Germany, Japan, the US, and the UK. In terms of the aggregate index, the US and UK stock markets seem to present the highest comovement across time and frequencies while the Japanese market shows a low degree of comovement with the other markets. At the sectoral level, the weak comovement of Japan with other countries is present while Germany, US, UK show a significant comovement at lower frequencies. Karim and Majid (2009) assess the stock market integration among the emerging stock markets of Indonesia and its major trading partners (Japan, US, Singapore, China). Their paper employs autoregressive distributed lag (ARDL) approach to cointegration method by taking weekly stock market data from 1998 to 2007. The results show that the Indonesian stock market is cointegrated with the stock markets of the US, Japan, Singapore and China. Aktan et al. (2009) study the emerging market indices of Brazil, Russia, China, India, Argentina (henceforth, BRICA) by investigating the linkages of these markets and their relations with the US market. This investigation employs the vector autoregression (VAR) technique and Granger causality tests in order to find evidence of a short run relationship between these markets by using daily data from January 2002 to February 2009. The results show that the most integrated markets were Russia and Brazil; and the least integrated ones were China and Argentina.

Caporale and Spagnolo (2010) demonstrate a tri-variate VAR-GARCH (1,1) –in-mean model to examine the linkages between the stock markets of three Central and Eastern European Countries (CEECs), namely the Czech Republic, Hungary, Poland and the UK and Russia. In consequence, there is a significant comovement (interdependence) of these CEEC markets with both the Russia and the UK. Mondli and Patel (2010) study with various alternative techniques the comovement among the selected developed stock markets and the emerging stock markets of the world by using the daily index data for the time period July 1997 to June 2008. By applying cointegration technique for the market pairs in both short-run and long-run they examine stock market indices of India (SENSEX), Hong Kong (HANSENG), Mexico (MXX), Russia (RTS), Brazil (BVSP), UK (FTSE-100) and US (DJIA and NASDAQ). They find that MXX, DOWJONES and NASDAQ are the least dependent on other markets, whereas DOWJONES is the most influential market. Taş and Tokmakçioğlu (2010) investigate stock market cointegration focusing on the market efficiency perspective. 11 emerging stock market indices are tested with Johansen cointegration technique, using weekly data for the period between January 1998 - December 2008 and for the sub-period of January

2002 - December 2008. The results show that in the long-term, Czech and Indian markets affect Turkish stock markets. On the other hand, changes in Argentinean, Indonesian and Hungarian markets affect Turkey in an inverse way. Furthermore, Brazilian stock market affects Mexican, Israeli and Indian stock markets in a parallel way, but Korean, Indonesian and Hungarian markets in an inverse way.

Ali et al. (2011) show the comovement of Pakistan's Equity Market with the markets of India, China, Indonesia, Singapore, Taiwan, Malaysia, Japan, USA and UK by using cointegration tests on monthly stock prices from the period of July 1998 to June 2008. Their conclusions indicate that even though there is no comovement of Pakistan's equity market with the markets of the UK, the USA, Taiwan, Malaysia and Singapore, the stock price of Pakistan equity market moves together with the stock prices of India, China, Japan and Indonesia. Panpura and Pantel (2011) examine the short-run causal link among equity markets in order to better understand how shocks in one market are transmitted to the others. They study the comovement of Indian stock market (BSE Sensex) index with 10 developed and developing countries stock market indices employing daily index prices for the period of July 1997 to December 2009. Their results show that SENSEX has highest the correlation with BVSP (98%) among all the pairs. Furthermore, SENSEX is affected by HANGSENG, STI, DJIA, FTSE and DAX. Besides, SENSEX causes SCI, BVSP, NIKKEI, KOSPI and AORD. Gallegati (2012) uses a wavelet based approach to test the presence of contagion during the Great Recession. The findings show that all stock markets have been affected by the US subprime crisis whereas Brazil and Japan are the only countries where contagion is observed at all frequencies.

Madaleno and Pinho (2012) assess the time varying pattern of price shock transmission through stock market linkages by using continuous wavelet methodology and wavelet coherence. Their findings indicate that the relationship among indices is strong but not homogenous across the time period. On the other hand, results favor that the markets, which are closer geographically and economically, exhibit higher correlation and short-run comovements which is mostly confined to long-run fluctuations favor contagion analysis. Blackburn and Chidambaran (2013) explain world stock market comovement of 23 developed and 10 emerging countries over the 30 year period of 1980-2010 by using correlation analysis. They find that the stock return comovement increases substantially from the mid-1990s to 2010 in both developed and emerging markets. Finally, the recent paper by Ftiti et al. (2014) examines the comovement dynamics between OECD countries with the US and Europe by

applying evolutionary co-spectral and wavelet analysis. The findings are that there is a long-run comovement between some of the Greece, Netherland, Norway, Portugal, Spain, Sweden, Italy and the US stock market indices and also that this long-run comovement had specifically increased during the beginning of the 90s and during the subprime crisis in 2007.

### **3. Data and Methodology**

This part consists of two sections: the data and the methodology. It aims to find the stock market comovements in emerging countries by analyzing Causality and Wavelet Methods.

#### *3.1. The Data*

This study encompasses data for weekly closing stock market index pricing which is covering the period of January 2003 till March 2014. The sample consists of 585 observations for each country's stock market acquired from the websites of Yahoo Finance and Bloomberg. Weekly data, which is used due to avoid nonsynchronous trading problems arising from different operating hours and time zones, is useful. For this reason, weekly data is used in this study. The indices used for the stock markets of the US, Turkey, China, Russia, Brazil, India, South Africa and Indonesia are SPX index, XU100 index, SCHOMP index, INDEXCF index, IBOVESPA index, SENSEX index, JALSH index and JCI index.

#### *3.2. Methodology*

##### *3.2.1. Wavelet Analysis*

The measurement of comovement among economic variables is key in several fields of economics and finance, namely in business cycle analysis, in asset allocations or in risk managements vice versa.

Wavelet is a designation of the finite-energy functions with localization properties used very efficiently to represent transient signals. Chui (1992) points out that efficiency means only a small finite number of coefficients are needed to represent a complicated signal. In contrast with the sinusoidal functions of infinite extent (big waves), 'wavelet' implies a 'small wave'. The wavelet transform is a tool that cuts up data or functions or operators into different



frequency components, and then studies each component with a resolution matched to its scale.<sup>2,3</sup>

Wavelet analysis merges both approaches, in the sense that both time and frequency domains are taken into account. Through wavelet analysis one can assess simultaneously how variables are related at different frequencies and how such relationship has evolved over time, allowing the capture of non-stationary features. This is a distinct and noteworthy aspect as both time and frequency varying behavior that cannot be captured using previous approaches.<sup>4</sup>

Mathematically, the wavelet transform decomposes a time series in terms of some elementary functions,  $\varphi_{\tau,s}(t)$ , which are derived from a time-localized mother wavelet  $\varphi(t)$  by translation and dilation Percival and Walden (2000). Wavelets grow and decay in a limited time period and are defined as  $\varphi_{\tau,s}(t) = \frac{1}{\sqrt{s}} \varphi(\frac{t-\tau}{s})$ , where  $\tau$  is the time position (translation parameter),  $s$  is the scale (dilation parameter), which is related with the frequency, and  $\frac{1}{\sqrt{s}}$  is a normalization factor to ensure that wavelet transforms are comparable across scales and time series. To be a mother wavelet,  $\varphi(t)$ , must fulfill certain criteria: it must have zero mean,  $\int_{-\infty}^{+\infty} \varphi(t) dt = 0$ ; its square integrates to unity,  $\int_{-\infty}^{+\infty} \varphi^2(t) dt = 1$ , which means that  $\varphi(t)$  is limited to an interval of time; and it should also satisfy the so-called admissibility condition,  $0 < C_{\varphi} = \int_0^{+\infty} \frac{|\varphi(\omega)|^2}{\omega} d\omega < +\infty$  where  $\varphi(t)^{\wedge}$  is the Fourier transform of  $\varphi(t)$ .

The continuous wavelet transform of a time series  $x(t)$  with respect to  $\varphi(t)$  is given by the following convolution

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t) \varphi_{\tau,s}^*(t) dt = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \varphi\left(\frac{t-\tau}{s}\right)^* dt$$

Where  $*$  denotes the complex conjugate.

As with its Fourier counterpart, there is an inverse wavelet transform, defined as:

$$X(t) = \frac{1}{C_{\varphi}} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \varphi_{\tau,s}(t) W_x(\tau, s) \frac{d\tau ds}{s^2}$$

<sup>2</sup> For further information see Percival and Walden (2002); Chui (1992). The article use the term ‘wavelet’ as a small wave.

<sup>3</sup> For further information please check Daubechies (1992).

<sup>4</sup> For further information please check Gençay et. al (2001); Rua (2010); Barunik et. al (2011); Ftiti et. al (2014)

This allows the recovering of the original series,  $x(t)$ , from its wavelet transform by integrating over all scales and time positions. Likewise in Fourier analysis, several interesting quantities can be defined in the wavelet domain. For instance, one can define the wavelet power spectrum as  $|W_x(\tau, s)|^2$ . It measures the relative contribution at each time and at each scale to the time series' variance. In fact, the wavelet power spectrum can be integrated across  $\tau$  and  $s$  to recover the total variance of the series as follows

$$\sigma_x^2 = \frac{1}{C_\varphi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} |W_x(\tau, s)|^2 \frac{d\tau ds}{s^2}$$

Another quantity of interest is the cross-wavelet spectrum which captures the covariance between two series in the time-frequency space. Given two time series  $x(t)$  and  $y(t)$ , with wavelet transforms  $W_x(\tau, s)$  and  $W_y(\tau, s)$  one can define the cross-wavelet spectrum as  $W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s)$ . The cross-wavelet spectrum is given by,

$$\rho_{xy}(\tau, s) = \frac{\mathcal{R}(W_{xy}(\tau, s))}{\sqrt{|W_x(\tau, s)|^2 |W_y(\tau, s)|^2}}$$

The wavelet-based measure  $\rho_{xy}(\tau, s)$  allows one to quantify the comovement in the time-frequency space and also helps to assess over which periods of time and frequency, the comovement is higher.<sup>5</sup>

### 3.2.2. Causality

The Granger causality test indicates whether the past changes in  $x(y)$  have an impact on current changes in  $y(x)$  over a specified time period. Nevertheless, these test results can provide the results on causality over all frequencies. Furthermore, Geweke's linear measure of feedback from one variable to another at a given frequency can provide detailed information about feedback relationships between stock market indices over different frequency bands.

By using a Fourier transformation method in order to apply VAR model for  $x$  and  $y$  series, the Geweke's measure of linear feedback from  $y$  to  $x$  at frequency  $\omega$  is defined as:

$$M_{x \rightarrow y}(\omega) = \log \left[ \frac{2\pi f_x(\omega)}{| \varphi_{11}(\varepsilon^{-\omega i}) |^2} \right] = \log \left[ 1 + \frac{| \varphi_{12}(\varepsilon^{-\omega i}) |^2}{| \varphi_{11}(\varepsilon^{-\omega i}) |^2} \right]$$

<sup>5</sup> See the overview in Rua (2010); Rua (2012).

If  $|\phi_{12}(e^{-i\omega})|^2 = 0$ , then Geweke's measure will be zero, then y will not Granger cause x at the frequency  $\omega$ . Breitung and Candelon (2006) mention this relationship between x and y in the VAR equation:

$$x_t = \alpha_1 x_{t-1} + \dots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \dots + \beta_p y_{t-p} + \varepsilon_{1t}$$

The null hypothesis tested by Geweke,  $M_{y \rightarrow x}(\omega) = 0$  corresponds to the null hypothesis of  $H_0: R(\omega)\beta = 0$  where  $\beta$  is the vector of the coefficients of y and  $R(\omega)$  is the matrix of sines and cosines.

Breitung and Candelon (2006) simplify Geweke's null hypothesis so that a usual F- statistics can be used to test causality in a frequency domain. Therefore, this study uses Breitung and Candelon's (2006) version of Geweke (1982)<sup>6</sup>.

## 4. Empirical Findings

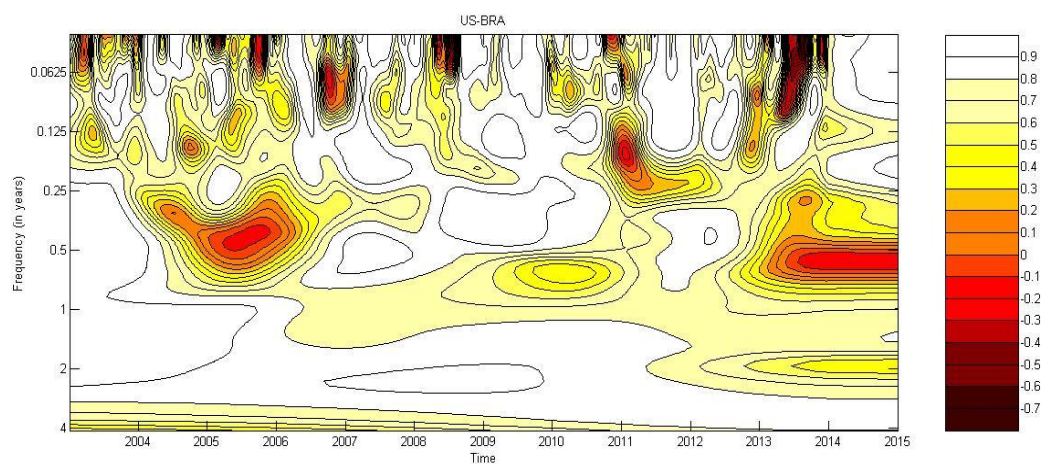
### 4.1. Wavelet Comovement Analysis Results

As a continuation of the results performed via Matlab software, the figures below are able to show the comovement between two variables coming from the countries' stock market data sets by using wavelet method. The important point of this method can be referred that it enables us to check the power of the movements of the variables in short and long runs. Thus, it makes the interpretations easier between the variables in order to check oscillation signals by a given time interval.

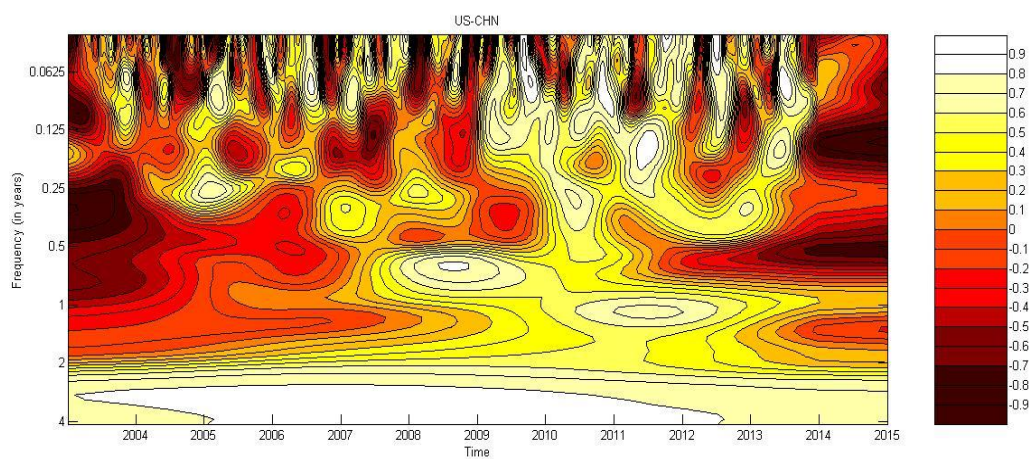
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<sup>6</sup> See the overview in Çelik and Haug (2012).

4.1.a. US vs. Brazil

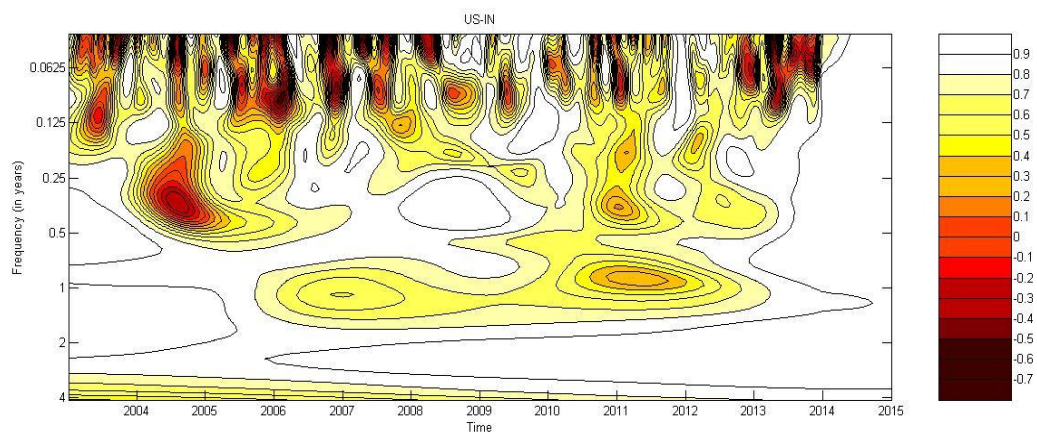


4.1.b. US vs. China

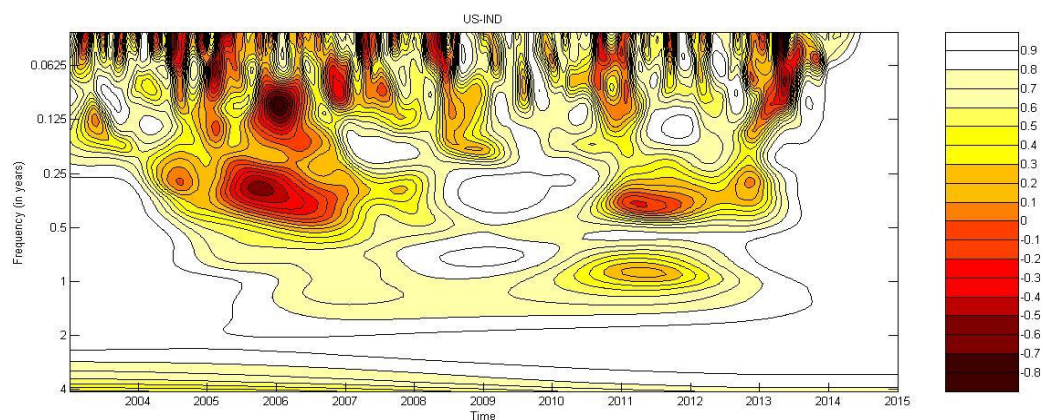


4.1.c. US vs. India

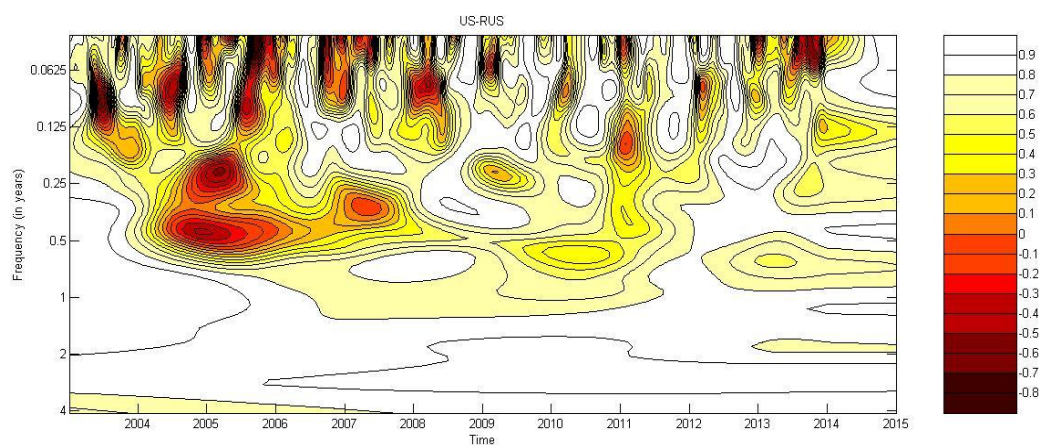




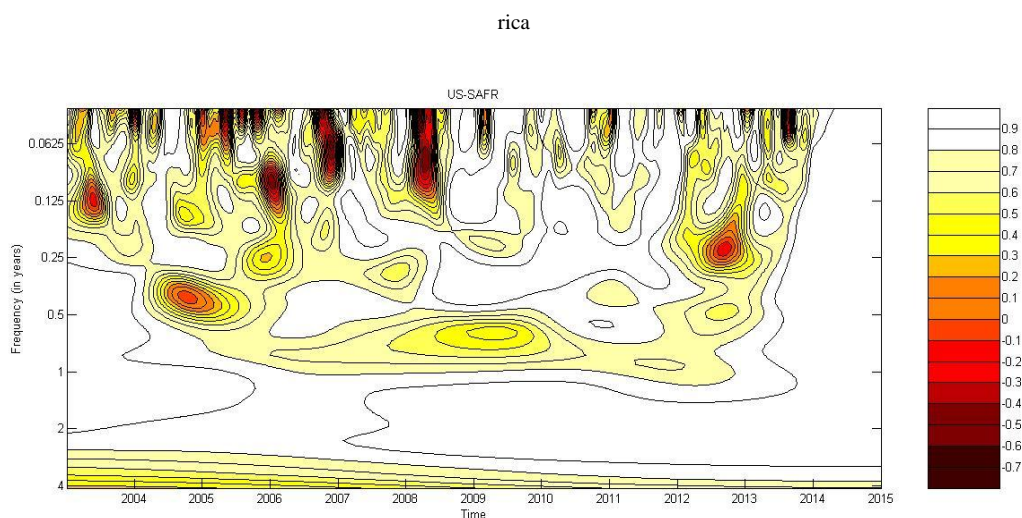
4.1.d. US vs. Indonesia



4.1.e. US vs. Russia



4.1.f. US vs South Af



4.1.g. US vs. Turkey

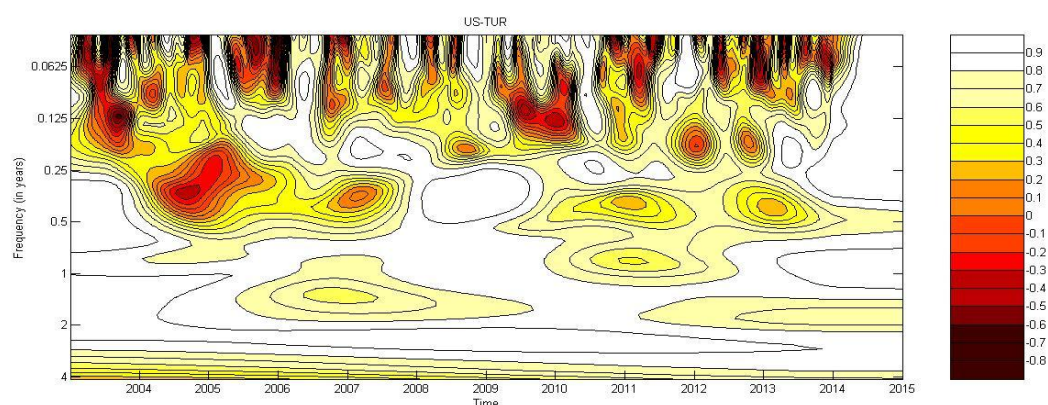


Figure 4.1 - Wavelet Comovement Power Spectrums for the US and the Selected Countries

Wavelet analysis is presented for all probable country pairs for the purpose of assessing stock market comovements (namely US and Brazil; US and China; US and India; US and Indonesia; US and Russia; US and South Africa; US and Turkey). Wavelet analysis is presented through a contour plot, involved as three dimensions where the figure is colored with various colors so as to read the results easily. The horizontal axis refers to time while the vertical one refers to frequency. To ease interpretations of the plotted figures, the frequency is converted to time units (years). The white colored areas represent the high degree oscillations whereas the hot colored ones correspond to low degrees in a surface plot. Each layers of the color bar, located in the right hand side of the figure, gives the degree of those signals from

the hot colors to white colors. Simply, the dark areas denote the weak comovements where the light areas denote the strong comovement between the variables. Hence, the series can be checked if they move together or not, or, if the strength of the comovement changes across frequencies over time.<sup>7</sup>

The figure above presents the country pairs one by one in terms of the stock market indices. The sub figure of the Figure 4.1, which is the Figure 4.1.a gives the wavelet results of the US and Brazil. One can conclude that the stock market activity of the US and Brazil seem to present weak but significant comovement at lower frequencies in the beginning of the sample period, and then the degree of the comovements seem to spread to all frequency levels after the year 2006. Furthermore, when looked at pre-2008 and post-2008, results indicate that there is a significant and high comovement however, during the Great Recession there is a comovement in an opposite way. In general, highly positive comovement has been observed between the US and Brazilian stock markets.

One of the interesting results as seen in the Figure 4.1.b is a weak comovement at long term fluctuations whereas at high frequencies the US has a counter-effect with China. After the global crisis, even though both the US and China were affected, China moved the opposite direction in stock market movements causing a negative degree of comovements with the US. The episode in question provides negative or low degree of comovements because there is a cash outflow from the US. That means money is coming into China.

Focusing now only on the US, India, Russia, Indonesia and South Africa, which are the Figures 4.1.c, 4.1.d, 4.1.e and 4.1.f, one general result can be concluded. There are strong comovements at high level frequencies around the mid of the sample period, but then, there is an increasing comovement at long term fluctuations that extended to all degree of frequencies after the year 2009 for all country pairs in question. Especially, after the initiation of 2012, we find evidence of a strong comovement at all degrees of frequencies. During crisis time, counter effect movements are observed. Note that between the US and Russia, it is shown that there were high comovement at all frequencies since 2012 at almost all frequencies. This observation is remarkable when considering the BRICS countries' economic policies and political issues.

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<sup>7</sup> See more Rua and Nunes (2009).

In the Figure 4.1.g, the US and Turkey stock markets seem to present quite a high degree of comovements across time at almost all frequencies. Especially, after the crisis, this significant comovement can be notably observed for all frequency levels since the positive degree of comovement has been spread to all frequencies in the time frequency space. There are some local points that represent a negative degree of comovement meaning while one country loses its cash flows, the other one increases its cash flows. So in an economic sense, they move in the opposite direction. But, in general, the comovements of the stock markets between the US and the Turkey are significant over the entire sample period as well as between the other country pairs with the US.

#### *4.2. Causality Tests' Results in Frequency Domain*

##### *4.2.1. Frequency Causality Test Results*

Frequency domain causality presents the test results with an observation of the indicators at given frequency levels in a given time. The test results of the frequency domain causality are represented from the figure and its sub figures below. These figures report the test statistics along with their 5% critical values and 10% critical values for all frequencies. High frequencies correspond to short periods and the low ones represent long periods. Apart from traditional interpretation, the test procedures of the frequency domain follow the reverse path on a vertical axis such as short term fluctuations at the right end and long term movements at the left. The analysis supportsevidence that there is a causal relation or there is an effect on stock market existence in any frequency level.

The figures beneath the page give relations between the variables by checking them with their given critical values. To this end, the red broken line represents a 5% critical value where the black broken one represents 10%. Above these lines mean that the results of the causality tests in the frequency domain are significant.

The Figures 4.2.1a, 4.2.1b, 4.2.1c, 4.2.1d show that the test results of bivariate causality in frequency domain are not that good for the frequency levels in the long run. On the other hand, while taking the figures one by one in order to make an ease interpretation, it can be said that the null hypothesis of  $IBOV \rightarrow SPX$  is rejected at 0.05 significance level in the Figure 4.2.1a. But this situation is not relevant for the entire frequency interval. In particular, the rejection of the null hypothesis takes place for high frequencies ,which is in the short run,



while  $SPX \rightarrow IBOV$  is only rejected in the range around 0.3 corresponding to the long run. At 0.10 level, the significance persists for  $IBOV \rightarrow SPX$  at high frequencies in the short term.

In the Figure 4.2.1b, the causal relations obtained in the bivariate model is valid for INDEXCF to SPX in the range interval [0.5, 3] where in the Figures 4.2.1c, and 4.2.1d, no predictable results are observed – except 4.2.1d before [0.5] level of significance - since the test accepts the null hypothesis of no causal relation not only in between JALSH and SPX but also in between SPX and JCI.

Inversely, in the Figure 4.2.1e the null hypothesis of no predictability is rejected in almost all frequency levels in the range [0, 3] except for around 1. Therefore, it can be predictable as SHOMP causes SPX at 5% and 10% significance levels.

In Figure 4.2.1f the null hypothesis of no conjecturable link is rejected for almost all frequencies, except for 0.5, with a significance level of 0.05. Due to the fact that the right hand side of the horizontal line gives the short-term, this frequency range corresponds to a cycle length in between many quarters, which means from the short to long run.

The Figure 4.2.1g shows that there is a predictability at frequencies less than 1.5 at 5% significance from SPX to XU100. The resulting sign that one-sided causal relation between SPX and XU100 means that while SPX causes XU100 at 5% significance level, in the long run with lower frequencies XU100 accepts the null hypothesis of no causal relation with SPX.

Figure 4.2.1a

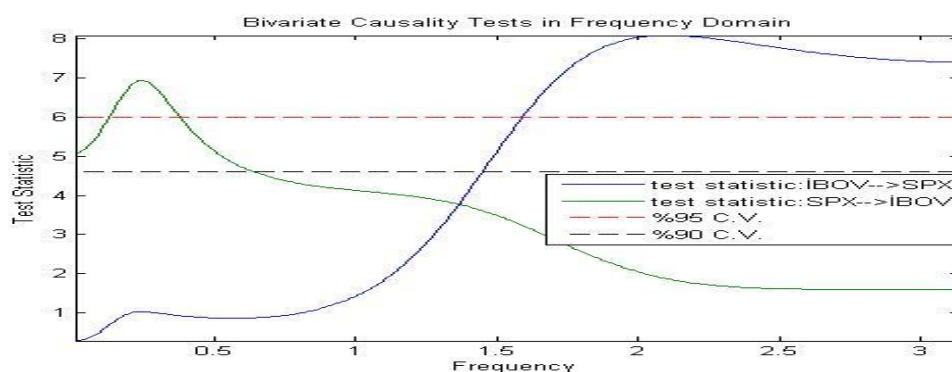


Figure 4.2.1b

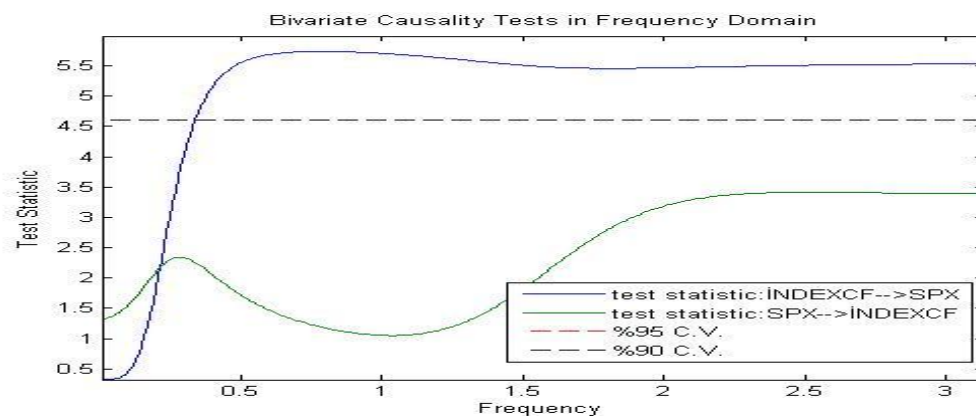


Figure 4.2.1c

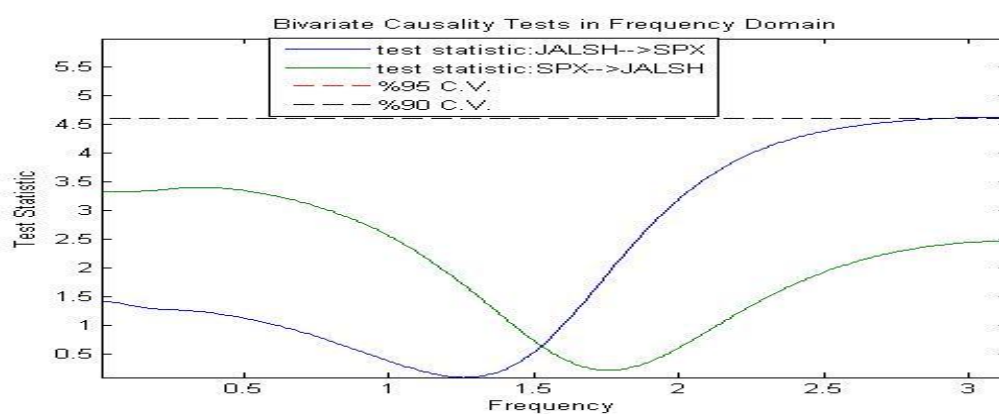


Figure 4.2.1d

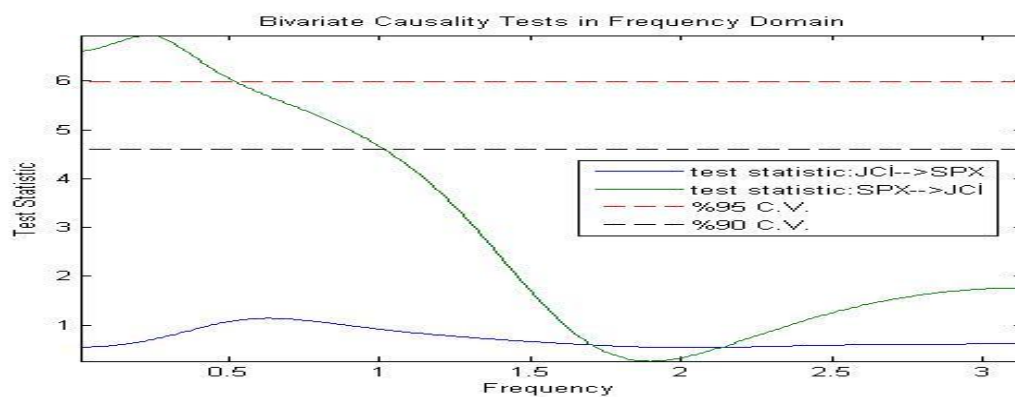


Figure 4.2.1e

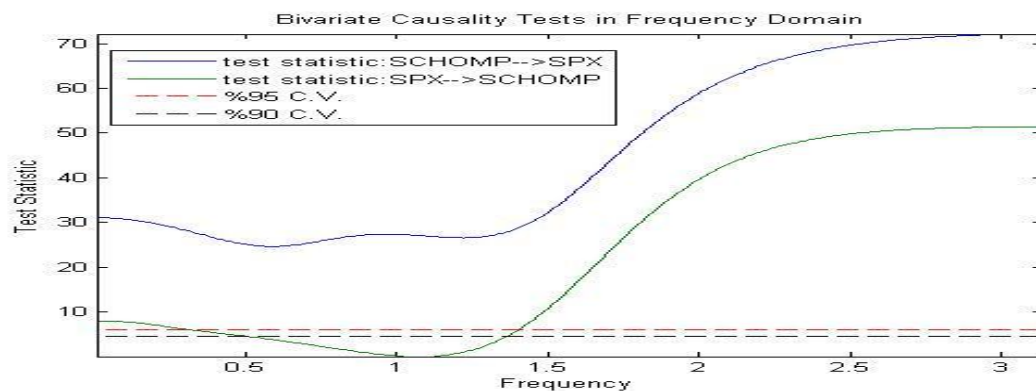


Figure 4.2.1f

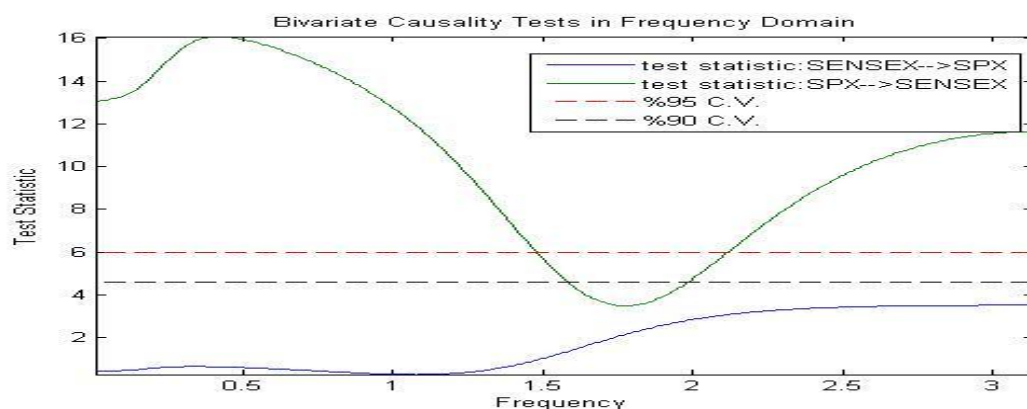


Figure 4.2.1g

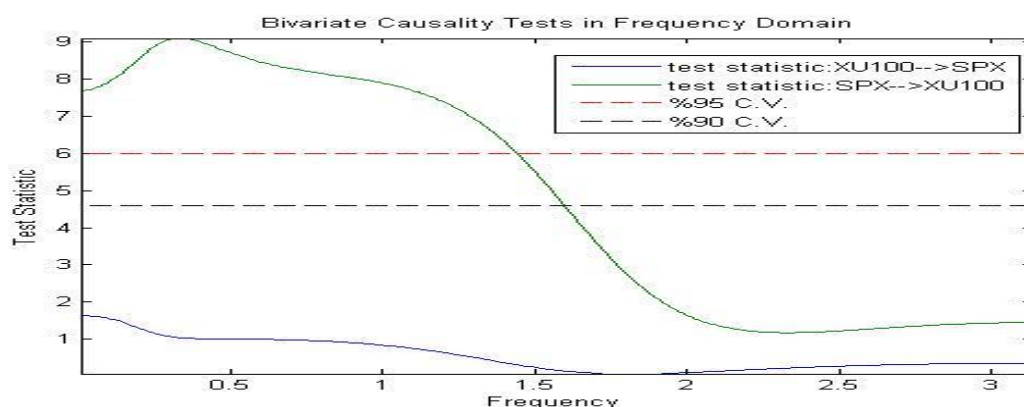


Figure 4.2.1 – Frequency Domain Causality Test Results of Stock Market Indexes according to the Countries, 2003-2014

Table 4.2.2 Unit root test

		<b>t statistic</b>	<b>%1 critical value</b>	<b>%5 critical value</b>	<b>%10 critical value</b>	<b>Prob.*</b>
SPX	intercept	-0.573811	-3.441337	-2.866279	-2.569353	0.8734
	Intercept and trend	-1.072226	-3.973874	-3.417546	-3.131192	0.9314
IBOV	intercept	-2.023933	-3.441337	-2.866279	-2.569353	0.2766
	Intercept and trend	-1.486812	-3.973874	-3.417546	-3.131192	0.8333
INDEXCF	intercept	-2.091707	-3.441337	-2.866279	-2.569353	0.2482
	Intercept and trend	-1.864880	-3.973874	-3.417546	-3.131192	0.6714
JALSH	intercept	0.130648	-3.441337	-2.866279	-2.569353	0.9678
	Intercept and trend	-1.762300	-3.973874	-3.417546	-3.131192	0.7218
SENSEX	intercept	-1.215337	-3.441337	-2.866279	-2.569353	0.6694
	Intercept and trend	-2.405184	-3.973874	-3.417546	-3.131192	0.3764
XU100	intercept	-1.520472	-3.441337	-2.866279	-2.569353	0.5227
	Intercept and trend	-2.617864	-3.973874	-3.417546	-3.131192	0.2724
JCI	intercept	-23.96774	-3.441318	-2.866270	-2.569348	0.0000
	Intercept and trend	-24.15782	-3.973847	-3.417533	-3.131184	0.0000
SCHOMP	intercept	-12.94541	-3.441357	-2.866287	-2.569358	0.0000
	Intercept and trend	-13.00134	-3.973901	-3.417559	-3.131200	0.0000

#### 4.2.2 – Augmented Dickey Fuller unit root tests

We apply the ADF unit root test to determine whether the whole data are stationary or not. Intercept and intercept and trend with automatic selection - Schwarz Info Criterion - are both examined. The null hypothesis is that the data has unit root. If we observe that the test statistic is smaller than critical values, we can reject the null and claim that our variable is stationary. Or when the p-value is less than or equal to the 5% significance level, we can reject the null hypothesis.

SPX, IBOV, INDEXCF, JALSH, SENSEX and XU100 have unit root, the series are not stationary. Whereas the ADF test is used at level form of JCI and SCHOMP and both of them are stationary. We do not need to apply Granger causality because of the ADF test results. Only if all of the series are stationary, Granger causality test can be performed.

#### 4.2.3. Geweke Feedbacks

In the last part of this section, Geweke Analysis' results of the countries with respect to the stock markets have been tested. Geweke's measure of linear feedback is used to test for the causality in the following sub figures of the Figure 4.2 in order to examine the percentage of the variance of all stock market indices (including Turkey, China, Brazil, South Africa, India, Indonesia and Russia) with the US stock market indices.

SENSEX, SCHOMP, XU100, JALSH, JCI, INDEXCF and IBOV are explained by SPX mostly at high frequencies. Firstly, it should be reported from the Figure 4.2.3a that SPX is not able to explain IBOV in the very short run, but in the long run the percentage of variance of IBOV explained by SPX reached 50% at a frequency level around 1.5. On the other hand,

the test results of SCHOMP explained by SPX are pretty good since the percentage of variance of SCHOMP explained by SPX is 100% until reaching the 2.5 frequency level, which corresponds to the short run. Even if the percentage is decreasing after the 2.5 frequency, the results are still strong in contrast with the other test results.

On the other side, both JALSH, JCI and INDEXCF give similar results to each other since the highest percentage of significant variance(25%) of JALSH, JCI, and INDEXCF were explained by SPX at a frequency level of around 1 while the second highest percentage of estimates is 20% at a frequency level of 2.5.

Figure 4.2.3a

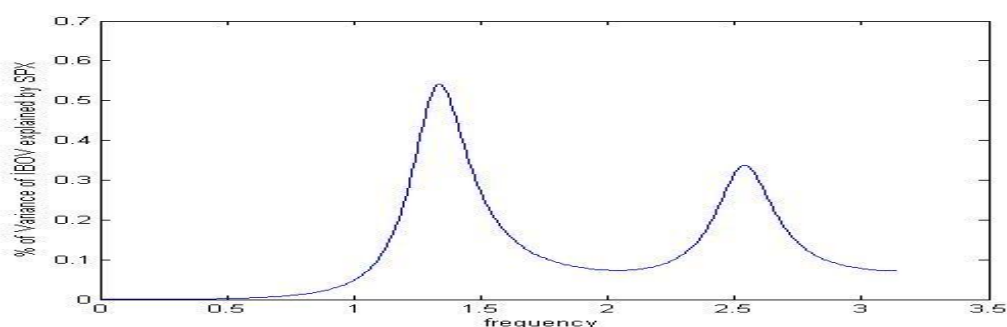


Figure 4.2.3b

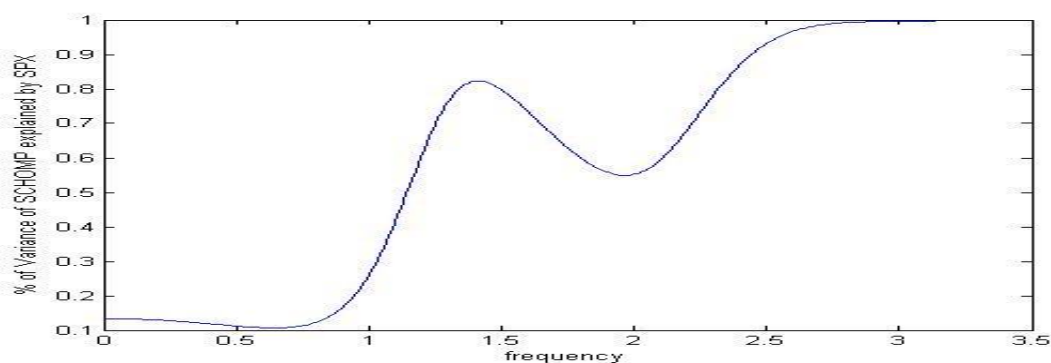


Figure 4.2.3c

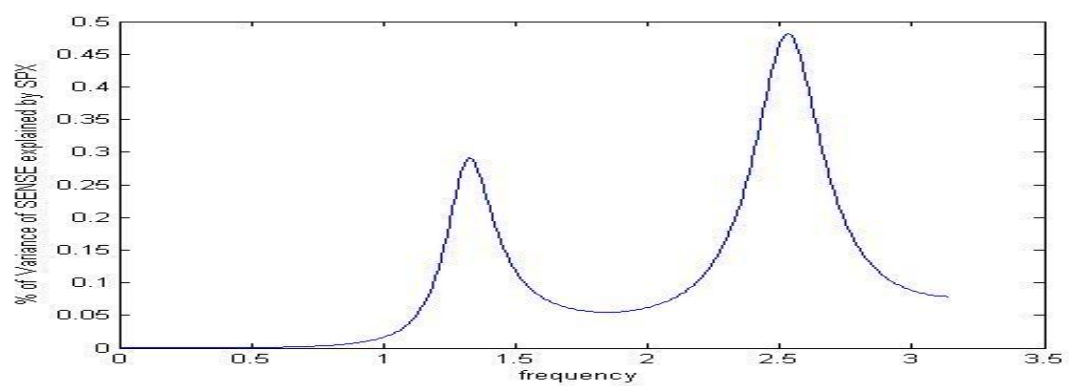


Figure 4.2.3d

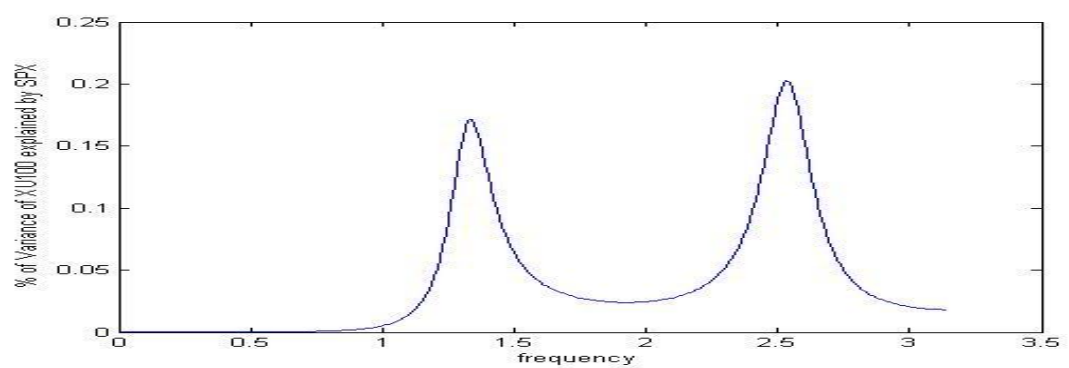


Figure 4.2.3e

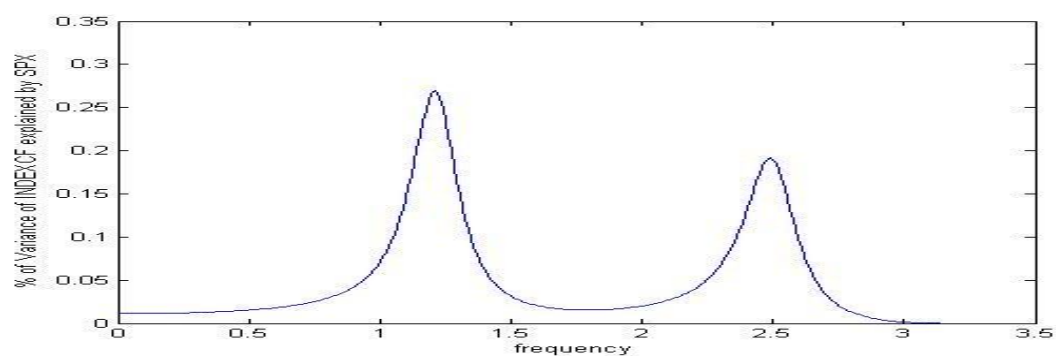


Figure 4.2.3f

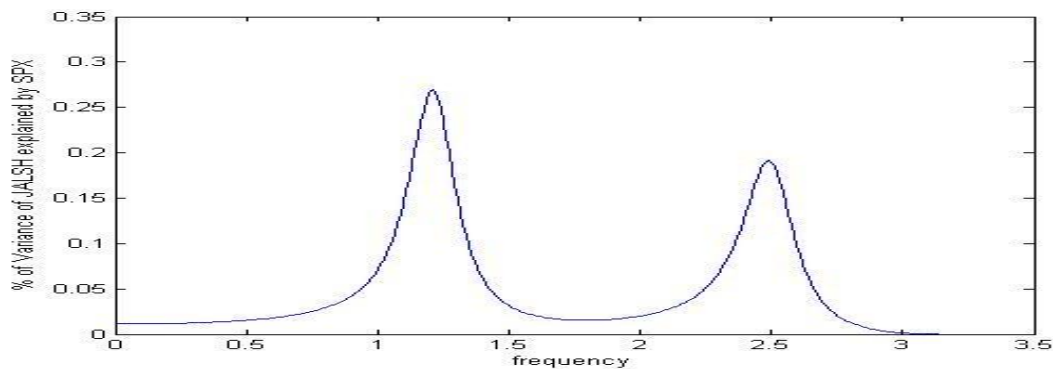


Figure 4.2.3g

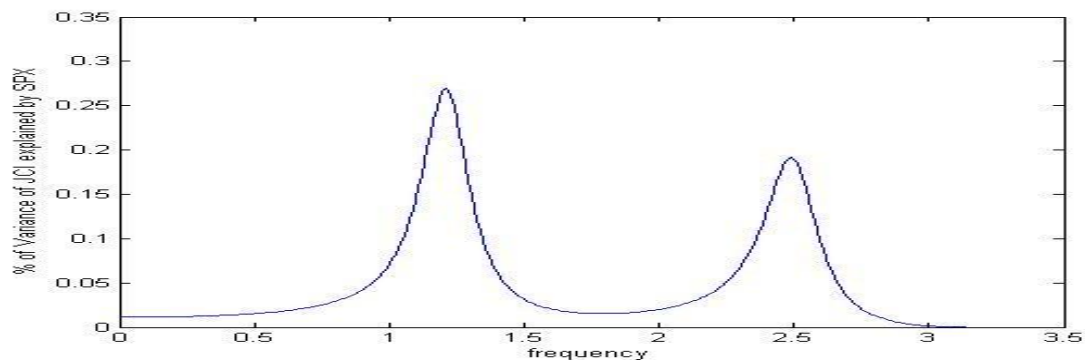


Figure 4.2 – Geweke Feedbacks of the Countries' Stock Market Indexes

## 5. Conclusion

This paper revisits the comovements of stock market indices including the countries: the US, Turkey, China, Russia, India, Indonesia, South Africa and Brazil (namely; SPX, XU100, SCHOMP, INDEXCF, SENSEX, JCI, JALSH, IBOV-SPA). The main theme is to assess the movements of stock markets.

Causality tests both in time and frequency domains and wavelet analysis are conducted in order to compare the results. The entire test results indicate the sameresults and substantiate

each other. The results show that US affects Turkey, Indonesia, India and Brazil at low frequencies, which is the long term while S. Africa, Brazil and Russia affect US at high frequencies. However China affects the US at all frequency levels. The US and China have cause and effect relationships while the US and S. Africa do not have a cause and effect relationship in general. The comovements of India, Indonesia, China, and Turkey with the US stock market are stronger than the comovements of Russia, S. Africa and Brazil with the US stock market. In general, the comovement between stock markets is stronger at high frequencies. Therefore, short term or long term movements should be taken into account to address international portfolio diversification issues. We also observe that the strength of the comovement in the time-frequency band varies across countries. All these results highlight the importance of taking into consideration the comovements of stock markets in designing economic policies while considering the role of financial markets in a capitalist system. Although, financial markets provide valuable data in high frequencies, and much earlier than many economic variables, we should not disregard the importance of the real economy and data that is announced with a certain lag. Moreover, there should be attempts to bridge the gap between the financial markets and the real economy rather than just letting a crisis take its course and cause damage to the system; which is hardly recoverable over a long period of time. Hence, the stock market indices should be followed carefully as well as their influence on the real economy. This paper argues that further research is needed to find a way to examine the linkages between high frequency financial market data and low frequency real economic variable data.

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